The Effect of Faculty Research on Student Achievement

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Abstract: The effect of faculty research on university student learning has long been the subject of intense debate. Previous studies have been limited in informing this debate because they use subjective or non-standardized measures of university student learning, focus on correlation rather than causation, and lack generalizability. Relying on unique, nationally representative data on students and faculty from four-year research universities in China and Russia as well as an identification strategy that utilizes within-student variation, we estimate the impact of faculty research on objective, standardized measures of student achievement. Results show that faculty research has a negative and statistically significant impact on student achievement.

The effect of faculty research engagement on teaching quality and student learning has been the subject of intense debate for centuries (Humboldt 1970; Newman 1853; Feldman 1987; Hattie and Marsh 1996; Prince, Felder, and Brent 2007). Conventional wisdom among faculty and university administrators is that research complements teaching (Neumann 1992; Smeby 1998; Robertson and Bond 2001). By engaging in research, faculty can ostensibly provide students with up-to-date, advanced knowledge and stimulate positive attitudes towards learning (Neumann 1992). Others posit that, given trade-offs in the allocation of time and energy across research and teaching activities, faculty research engagement may have a negative or negligible effect on teaching quality and student learning (Fox 1992; Linsky and Straus 1975). Critics further argue that the higher pecuniary benefits and prestige tied with research as opposed to teaching may lead faculty to overinvest in research activities (Tuckman and Hagemann 1976; Cech 2003). They contend that universities need to prioritize teaching directly and not assume that a system that primarily rewards research engagement will naturally result in high-quality teaching (Nature Editorial 2010).

Five decades of empirical investigation have not settled the debate (Feldman 1987; Hattie and Marsh 1996; Prince, Felder, and Brent 2007; Figlio and Schapiro, 2017). Meta-analytic reviews of the quantitative literature find a "zero correlation" between research engagement and teaching quality (Hattie and Marsh 1996). Past studies are limited, however, in that they examine the relationship using subjective or non-standardized measures of teaching quality and student learning (Hattie and Marsh 1996; Galbraith and Merrill 2012). Most measures of student learning are self-reported, subject to bias (Galbraith and Merrill 2012; Shevlin et al. 2000; Felton, Mitchell, and Stinson 2004), and uncorrelated with student learning in the long run (Carrell and West 2010). An equally fundamental problem is that studies do not use causal identification strategies to estimate the impact of faculty research engagement on student learning. In particular, past studies do not account for a classic selection bias problem in the educational research literature: the non-random sorting of students across different instructors (Hanushek and Rivkin 2010). A third problem is that prior studies usually focus on one or a small number of institutions (Figlio and Schapiro 2017). The results of these studies therefore lack in generalizability.

The purpose of this study is to examine the impact of faculty research engagement on student achievement**.** We estimate impacts using a unique dataset that we collected from nationally representative (random) samples of undergraduate students in science, technology, engineering, and mathematics (STEM) majors in China and Russia. A strong foundation in STEM is believed to be important for national economic productivity and innovation (Augustine

2005). Policymakers and researchers from around the world have therefore made teaching and research in STEM majors a top priority (Augustine 2005; Lucena et al. 2008).

II. Data

The dataset was collected from nationally representative samples of Electrical Engineering (EE) programs in China and nationally representative samples of EE and Computer Science (CS) programs in Russia. In China, we first chose five provinces that represented China's northern (Beijing and Shandong), central (Henan and Shaanxi), and southern (Sichuan) regions as well as its economically more developed (Beijing ranked 2nd in GDP per capita out of 31 provincial-level administrative divisions), mid-developed (Shandong and Shaanxi ranked 10th and 14th) and less developed (Sichuan and Henan ranked 22nd and 24th) regions (National Bureau of Statistics of China 2015). From each of the five provinces, we took a simple random sample of 6 universities from a list of all universities in each province that offered bachelor's degree programs in CS and EE. In Russia, we took a simple random sample of 34 universities from a list of all universities nationwide that offered bachelor's degree programs in CS and EE. For both China and Russia, we further limited the sample to universities with CS and EE programs that taught math and physics courses to students in their first two years.[1] Altogether, we sampled 802 electrical engineering (EE) students from 28 public four-year universities in China and 580 EE and computer science (CS) students from 29 public four-year universities in Russia. In addition, we surveyed the faculty that taught students math and physics courses in the first two years of university.

[1] The math and physics courses were virtually all taught in the first two years of these bachelor's degree programs.

Students were surveyed and tested in late November and early December 2015, at the beginning of the third year of their undergraduate studies. Trained enumerators administered valid and reliable math and physics exams to students in a timed and controlled environment (Kardanova et al. 2016). We standardized exam scores using the mean and standard deviation (SD) of scores within each subject. After the exams were completed, students provided information about their age, gender, major, and socioeconomic background (Appendix Table 1).

Faculty were surveyed near the same time as students. We asked faculty to report the number of publications (defined as the total number of published academic journal articles, monographs, and edited volumes) from the last three years. Following the literature (Hattie and Marsh 1996), we used the average number of publications per year as a measure of faculty research engagement. We further log transformed this variable to account for the long tail in publication rates where most professors produce few publications and a few produce many. Details and summary statistics for the indicator are located in the Appendix (Appendix Table 2).

A range of faculty professional background characteristics were collected to serve as controls in our analyses. Faculty reported their age, gender, and educational background. They also reported their academic title, whether they were full or part time faculty, and years of teaching experience at the university level. Based on faculty responses, we created dummy variables for whether faculty attended elite universities for their terminal degree program, and whether they had a terminal degree major in the subject (math or physics) they were teaching. We further broke down the years of teaching variable into categorical dummies to allow for potential nonlinearities in the relationship between teaching experience and student achievement (Clotfelter, Ladd, and Vigdor 2007; see Appendix Table 2).

We matched students to their respective math and physics instructors. Following the economics literature, we created a composite faculty vector for each student that averaged all of the student's instructor characteristics weighted by the respective credit hours allocated to each instructor's course (E. Bettinger and Long 2005; E. P. Bettinger and Long 2010). Each student was thus observed twice in our dataset: once with a math score and composite math faculty vector and once with a physics score and composite physics faculty vector.

II. Statistical Approach

Our main specification was a cross-subject student fixed effects model that exploits variation across math and physics subjects within students. Cross-subject student fixed effects models minimize potential bias induced by the non-random assignment of students across classes and schools. We are thus able to better identify causal effect estimates by only utilizing the variation that exists across different subjects (e.g. math and physics) within the same student (Angrist and Pischke 2008). Cross-subject student fixed effects models are frequently used in the econometric literature (e.g. Dee 2005; Dee 2007; Clotfelter, Ladd, and Vigdor 2010; Kingdon and Teal 2010; Lavy 2015; Rivkin and Schiman 2015).

In our model, we compare outcomes within the same student in different subjects, controlling for other factors that may differ across these subjects. By utilizing this variation, the model controls for all factors which are constant across subjects and which may confound the relationship between faculty research engagement and student achievement. This includes unobserved student-level factors such as student innate ability and motivation. It also includes all administrative class and school level factors that do not vary across subjects, thus accounting for potential non-random assignment of students to administrative classes and schools. To further eliminate potential sources of selection bias, we controlled for a number of faculty characteristics that differed across math and physics within each student. We also accounted for preexisting variation in cross-subject achievement by controlling for the average math and physics achievement levels of cohorts of entering freshman in the same department.

In our specific context, the cross-subject student fixed effects model takes the first difference between math and physics subjects (scores and corresponding determinants) within each student. By doing so, the specification eliminates the confounding influence of unobserved subject-invariant factors. The specification is written as follows:

$$(y_{pi} - y_{mi}) = \beta(FR_p - FR_m) + \lambda(Z_p - Z_m) + \eta(X_i - X_i) + \gamma(A_{pi} - A_{mi}) + \kappa(S - 0) + (\mu_i - \mu_i) + (\epsilon_{pi} - \epsilon_{mi}) \quad (1)$$

where y_{mi} and y_{pi} are a student's standardized scores in math and physics. Similarly, FR_m and FR_p are the indicators for faculty research engagement for math and physics instructors. Z_m and Z_p consists of observed faculty-level determinants of student scores for math and physics. X_i is a vector of student characteristics that vary across students but not across subjects. A_{mi} and A_{pi} represent baseline achievement levels in math and physics. S is a dummy variable indicating whether the subject in question is physics (as opposed to math). u_i is an unobserved student effect that does not vary between subjects. Finally, ϵ_{mi} and ϵ_{pi} are student-level error terms. Non-subject specific student, administrative class, and school level characteristics (both observed and unobserved) are canceled out and do not induce bias in the estimation of β.

Conditional on a few assumptions, the student fixed effects model produces unbiased estimates of the effect of faculty research engagement (β). The first assumption is that the way in which faculty research engagement affects student performance is similar across both math and physics subjects. We included the subject (physics or math) dummy variable (S), to control for the situation in which faculty research engagement influences student achievement more in one subject than in the other. The second assumption is that the remaining error term $\epsilon_{pi} - \epsilon_{mi}$ in equation 1 is uncorrelated with the faculty research engagement $\beta(FR_p - FR_m)$. This assumption implies that unobserved student or faculty characteristics that vary across the two subjects should not be jointly correlated with faculty research engagement and student achievement (Schwerdt and Wuppermann 2011). To account for possible correlations, we control for preexisting variation in achievement levels across subjects. We also control for a number of faculty-level cross-subject factors. These factors are documented in the faculty level summary statistics in Appendix Table 2. We also adjust standard errors for clustering at the class level (Dee 2007).

As a robustness check, and for the sake of comparability with the existing literature, we also estimate the following ordinary least squares (OLS) model:

$$y_{si} = \beta FR_s + \lambda Z_s + \eta X_s + \gamma A_{si} + \kappa S + \mu_i + \epsilon_{si} \tag{2}$$

Equation 2 yields causal estimates of the effect of faculty research engagement on student achievement under the assumption of strong ignorability (Imbens and Rubin 2015). Namely, if y_{si} and FR_s, conditional on a rich set of student, class and faculty background characteristics including baseline test scores, are uncorrelated with the combined error term $\mu_i + \epsilon_{si}$, estimates of β capture the causal effect of faculty research engagement on student achievement. However, unobserved factors such as a student's motivation may still confound the relationship between faculty research engagement and student achievement. Like with the cross-subject student fixed effects analyses, we adjust standard errors for clustering at the class level.

Finally, we perform robustness checks to account for missing faculty data.[2] Specifically, we exclude administrative classes from our analytical sample if they were missing more than 20%, 15% and 10% of faculty. For each robustness check, we find effect sizes that are similar in magnitude and direction, albeit with reduced statistical significance due to the reduction in sample size.[3] Taken together, the robustness checks suggest that missing data only have a marginal influence on our main results.

III. Results

Results show that faculty research engagement has a negative and statistically significant effect on student achievement (Table 1). According to the student fixed effects analysis, a standard deviation (2.98 publications a year) increase in faculty publications reduces student achievement by 0.073 SDs (Column 1).[4]

Results are substantively the same under different specifications. Results using the untransformed publications per year variable are substantively similar to the results we get using the log-transformed variable (Table 2). Slight reductions in statistical significance are likely associated with the heavy tail of the distribution of the untransformed publications per year variable. The results from the OLS model are also largely consistent with the results from the student fixed effect model (Table 3). The coefficients on faculty research engagement are similar in effect size to those of the student fixed effects model for China, Russia, and both countries

[2] The faculty response rate was 87.9% for China and 85.5% for Russia. Most non-responders were on leave, had recently retired, or were visiting a foreign institution.
[3] Results omitted for the sake of brevity but available upon request.
[4] The reported R2 statistic only reflects the proportion of within-student variance explained. It does not report the variance reduction induced by adding the student fixed effects.

combined. The coefficients for both countries combined and for Russia are statistically significant at the 10% and 5% levels.

We also examined whether research engagement had nonlinear impacts on student achievement. We assessed potential nonlinearities with a component-plus-residual plot (White 1996). Figure 1 shows the plots with the log of publications per year on the horizontal axis. Given that the LOESS smoothed line is highly linear, we find no indication of a nonlinear impact.

Although smaller than the significant effect sizes typically reported in studies of pre-tertiary education, the estimated effect sizes reported in this study are non-trivial in the context of higher education. Multiple studies show that a one standard deviation increase in faculty value-added increases student achievement by 0.05 to 0.06 SDs (Carrell and West 2010; Hoffmann and Oreopoulos 2009). Furthermore, our results may be underestimates as student fixed effects estimates tend to control for too much variation in the dependent variable and are susceptible to attenuation bias arising from measurement error in the independent variable (Angrist and Pischke, 2008).

Our results provide the first systematic evidence that, in STEM disciplines at a wide range of universities in two key countries, there is a significant and non-trivial tradeoff between research and teaching. Policymakers and university administrators that are concerned about the tradeoff may wish to more closely monitor how to balance research and teaching activities within their institutions. On the one hand, they may wish to readdress the distribution of faculty incentives between teaching and research in an effort to find an optimal tradeoff. On the other hand, they may wish to continue the trend of hiring faculty that specialize in teaching or research, with the caveat that the presence of faculty that engage in both areas may serve other purposes such as attracting prospective students and faculty (Wood 1973).

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Figures and Tables

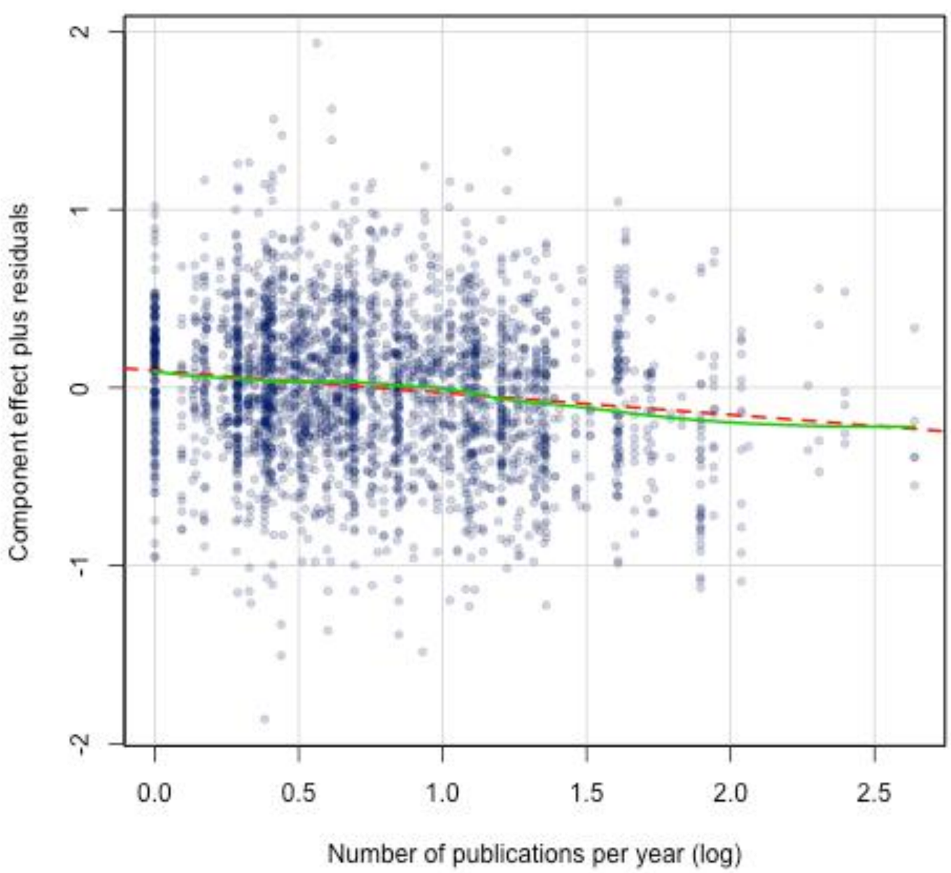

Figure 1: The component effect of publications per year (log) on standardized scores plus residuals. The dotted red line represents the component effect, and the solid green line is a LOESS line.

Table 1: The effect of faculty research engagement (publications per year, log transformed) on student achievement (student fixed effect model)

	(1)	(2)	(3)
	Student Fixed Effects Model (China + Russia)	Student Fixed Effects Model (China)	Student Fixed Effects Model (Russia)
Number of publications per year (log)	-0.115	-0.136	-0.138
	(0.046)	(0.067)	(0.065)
Physics subject dummy (opposed to math)	0.021	-0.019	-0.062
	(0.034)	(0.044)	(0.062)
Achievement levels of entering freshman (math and physics)	0.411	0.267	0.504
	(0.120)	(0.126)	(0.191)
Faculty level variables			
Female	-0.175	-0.142	-0.089
	(0.063)	(0.093)	(0.079)
Fulltime faculty	-0.037	-0.056	-0.042
	(0.084)	(0.144)	(0.101)
Faculty has PhD degree	0.102	0.061	0.402
	(0.093)	(0.104)	(0.383)
Full Professor (compared to Lecturer or RA)	-0.010	-0.078	-0.157
	(0.094)	(0.107)	(0.362)
Associate Professor (compared to Lecturer or RA)	-0.062	-0.035	-0.460
	(0.080)	(0.093)	(0.373)
Went to elite university for highest degree obtained	-0.119	-0.048	-0.124
	(0.070)	(0.120)	(0.099)
Majored in math or physics for highest degree	-0.029	-0.066	0.094
	(0.069)	(0.096)	(0.147)
Number of years teaching (middle tercile in country)	-0.124	0.086	-0.378
	(0.118)	(0.122)	(0.164)
Number of years teaching (upper tercile in country)	0.025	0.131	-0.092
	(0.081)	(0.114)	(0.109)
Constant	0.415	0.551	0.360
	(0.151)	(0.249)	(0.286)
Observations	2668	1570	1098
R2	0.051	0.031	0.130

Notes:
1. Standard errors in parentheses.
2. Standard errors corrected for clustering at the class level.
3. The R2 reported denotes the proportion of within-student variance explained. The total proportion of (within- and across-student) variance explained is above 0.75 for all 3 models.

Table 2: The effect of faculty research engagement (publications per year, not log-transformed) on student achievement (student fixed effect model)

	(1)	(2)	(3)
	Student Fixed Effects Model (China + Russia)	Student Fixed Effects Model (China)	Student Fixed Effects Model (Russia)
Number of publications per year	-0.042	-0.045	-0.052
	(0.018)	(0.025)	(0.023)
Physics subject dummy (opposed to math)	0.018	-0.025	-0.062
	(0.033)	(0.045)	(0.059)
Achievement levels of entering freshman (math and physics)	0.434	0.290	0.533
	(0.118)	(0.124)	(0.194)
Faculty level variables			
Female	-0.185	-0.151	-0.101
	(0.063)	(0.091)	(0.076)
Fulltime faculty	-0.045	-0.037	-0.038
	(0.085)	(0.154)	(0.098)
Faculty has PhD degree	0.112	0.072	0.429
	(0.095)	(0.105)	(0.399)
Full Professor (compared to Lecturer or RA)	-0.005	-0.082	-0.151
	(0.099)	(0.114)	(0.384)
Associate Professor (compared to Lecturer or RA)	-0.075	-0.034	-0.510
	(0.082)	(0.092)	(0.390)
Went to elite university for highest degree obtained	-0.129	-0.059	-0.125
	(0.071)	(0.121)	(0.101)
Majored in math or physics for highest degree	-0.039	-0.068	0.070
	(0.069)	(0.100)	(0.132)
Number of years teaching (middle tercile in country)	-0.125	0.078	-0.381
	(0.117)	(0.122)	(0.156)
Number of years teaching (upper tercile in country)	0.016	0.112	-0.102
	(0.083)	(0.117)	(0.110)
Constant	0.433	0.517	0.407
	(0.153)	(0.253)	(0.286)
Observations	2668	1570	1098
R2	0.054	0.030	0.140

Notes:
1. Standard errors in parentheses.
2. Standard errors corrects for clustering at the class-level.
3. The R2 reported denotes the proportion of within-student variance explained. The total proportion of (within- and across-student) variance explained is above 0.75 for all 3 models.

Table 3. The effect of faculty research engagement (publications per year) on student achievement (OLS regression controlling for the full set of covariates)

	(1)	(2)	(3)
	Student Fixed Effects Model (China + Russia)	Student Fixed Effects Model (China)	Student Fixed Effects Model (Russia)
Number of publications per year	-0.095	-0.096	-0.138
	(0.050)	(0.078)	(0.067)
Physics subject dummy (opposed to math)	0.028	-0.019	-0.062
	(0.034)	(0.050)	(0.065)
Achievement levels of entering freshman (math and physics)	0.420	0.251	0.504
	(0.126)	(0.151)	(0.198)
Student level variables			
Age	-0.036	-0.053	-0.019
	(0.016)	(0.024)	(0.015)
Female	-0.033	0.023	-0.124
	(0.040)	(0.052)	(0.057)
Father had gone to college	0.039	-0.010	0.064
	(0.044)	(0.088)	(0.049)
Mother had gone to college	0.038	0.060	0.041
	(0.053)	(0.092)	(0.068)
Household assets index	-0.021	-0.018	-0.026
	(0.018)	(0.022)	(0.023)
Faculty level variables			
Female	-0.148	-0.099	-0.089
	(0.059)	(0.082)	(0.082)
Fulltime faculty	-0.005	0.160	-0.042
	(0.091)	(0.318)	(0.105)
Faculty has PhD degree	0.048	0.026	0.402
	(0.100)	(0.112)	(0.397)
Full Professor (compared to Lecturer or RA)	0.032	-0.056	-0.157
	(0.110)	(0.128)	(0.375)
Associate Professor (compared to Lecturer or RA)	-0.001	0.030	-0.460
	(0.089)	(0.108)	(0.386)
Went to elite university for highest degree obtained	-0.101	-0.016	-0.124
	(0.070)	(0.121)	(0.102)
Majored in math or physics for highest degree	-0.031	-0.046	0.094
	(0.069)	(0.099)	(0.153)
Number of years teaching (middle tercile in country)	-0.098	0.124	-0.378
	(0.122)	(0.128)	(0.170)
Number of years teaching (upper tercile in country)	0.061	0.201	-0.092
	(0.086)	(0.124)	(0.113)
Constant	1.093	1.358	0.743
	(0.374)	(0.644)	(0.449)
Observations	2642	1544	1098
R2	0.516	0.382	0.395

Notes:
1. Standard errors in parentheses.
2. Standard errors corrected for clustering at class level.

The Effect of Faculty Research on Student Achievement

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Appendix

Appendix A: Sampling and Implementation Details

The national samples of universities represented the range of elite and non-elite institutions in each country. In China, "elite" universities were defined on the basis of their designation as Project 985 or 211 universities. Project 985 universities are the top 39 universities in China whereas Project 211 universities are the top 112 universities in China, and both have received preferential national government funding. In Russia, "elite" universities were defined as National Research Universities, "5-100" universities, and Federal universities. Altogether, we sampled 6 elite and 22 non-elite universities in China as well as 6 elite and 23 non-elite universities in Russia.

We next randomly sampled students within CS and EE departments within the sample universities. We first identified EE departments in China.[1] After identifying the EE departments, we randomly sampled 2 EE departments from each sample university.[2] We then randomly sampled 1 administrative group or "class" of year 3 (junior year) students within each department. All students within the sampled classes were selected for participation in the study.

Similarly, we identified CS departments and EE departments in Russia.[3] After identifying the departments, we randomly sampled 3 CS departments and 3

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[1] The EE departments in China included *Electrical Engineering, Electrical Engineering and Automation, Measurement and Control Technology and Instrumentation, Electronic Science and Technology, Electronic and Information Engineering, Electronic and Information Science and Technology, Communication Engineering, Optoelectronic Information Science and Engineering, Microelectronics Science and Engineering), and Automation*

[2] If there was only one EE department in the university, we sampled only that department.

[3] The CS departments in Russia include *IT and Computer Facilities, Informational Systems and Technologies, Applied IT, Program Engineering, Mathematics and Computer Science, Fundamental IT and Information Technologies, Software and Administration of Information Systems, Information*

EE departments from each university.[4] We then randomly sampled 1 administrative group or class of year 3 (junior year) students within each department.[5] All students within the sampled classes were selected for participation in the study.

The survey was conducted in late November and early December of 2015. Within each administrative class, one half of the sampled students were randomly chosen to take two closely proctored exams: math and physics. The math and physics exams each contained 35 items and lasted for 40 minutes. The different subject exams were given to examinees in random order to avoid fatigue-induced bias in exam results. Details about the construction and suitability of the math and physics exams can be found in Kardanova et al. (Kardanova et al. 2016).

After the exams were completed, students responded to a short questionnaire. Students were asked about their age, gender, major, parental education attainment, and several items of value in the home. We used the information on household and polychoric principal components analysis to create a proxy for wealth or socioeconomic status (Kolenikov and Angeles 2009). Student participation rates for both the questionnaire and the exams were extremely high (95% for China and 87% for Russia). Summary statistics for the student level variables are presented in Appendix Table 1.

Security. The EE departments in Russia include *Information and Communication Technology and Communication Systems, Design and Technology of Electronic Instrumentation, Radio Engineering, Electronics and Nanoelectronics, Electrical Power and Electric Engineering, Laser Equipment and Laser Technologies, Optics Engineering, Instrument Construction, Photonics and Optoinformatics*.

[4] If there were less than three EE departments in the university, we sampled all departments.

[5] In both China and Russia, we also sampled one class of year 1 (freshman) students from each department. The test scores for these freshman students served as control variables in our analyses.

Appendix B: Faculty Data

We collected faculty data in a follow up online survey after the main survey of students. All EE students in China and Russia and a subset of CS students in Russia are expected to take mandatory courses in math and physics in their first two years of university. By cross-referencing administrative records and a section of our student questionnaire where students wrote down the names of their math and physics instructors, we compiled a list of all faculty that had taught math and physics courses to the sample students in the previous years of college. We subsequently asked faculty members to answer a questionnaire. Faculty reported their gender, academic title, education background, whether they worked full time or part time, whether they had a PhD degree, and how much they published in the past 3 years. Summary statistics for these faculty level variables are in Appendix Table 2.

We then matched students to their respective math and physics instructors. In almost all cases, students took multiple courses in math and physics and were therefore matched to multiple math and physics instructors. Following the economics literature, we created one synthetic faculty member for each student for each subject(E. Bettinger and Long 2005; E. P. Bettinger and Long 2010). The synthetic faculty member for math averaged all of the student's math instructor characteristics weighted by the respective credit hours allocated to each instructor's course. Similarly, the synthetic faculty member for physics averaged all of the student's physics instructor characteristics weighted by the respective credit hours allocated to each instructor's course. These operations resulted in a dataset where each student was observed twice: once for math (with variables for math achievement and math faculty characteristics) and once for physics (with variables for physics achievement and physics faculty characteristics).

Appendix Table 1: Student level summary statistics

	Both countries			China			Russia		
	N	Mean	St. Dev.	N	Mean	St. Dev.	N	Mean	St. Dev.
Math subject test score	1382	0.000	1.000	802	0.441	0.933	580	-0.610	0.736
Physics subject test score	1382	0.000	1.000	802	0.368	0.976	580	-0.508	0.788
Grade 1 student achievement in math	1334	-0.193	0.843	785	0.429	0.450	549	-1.082	0.304
Grade 1 student achievement in physics	1334	-0.287	0.747	785	0.207	0.503	549	-0.993	0.384
Age	1369	22.012	1.236	789	22.336	1.099	580	21.572	1.276
Female	1382	0.269	0.444	802	0.296	0.457	580	0.233	0.423
Father has college education	1382	0.391	0.488	802	0.182	0.386	580	0.681	0.466
Mother has college education	1382	0.413	0.493	802	0.138	0.346	580	0.793	0.405
Household asset index	1379	-0.007	1.300	800	-0.608	1.251	579	0.823	0.821

Appendix Table 2: Faculty level summary statistics

	Both countries			China			Russia		
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	N	Mean	Std. Dev.
Number of publications per year (log)	619	0.810	0.674	277	0.760	0.626	342	0.851	0.709
Number of publications per year	619	1.953	2.984	277	1.721	2.675	342	2.141	3.205
Female	634	0.442	0.497	283	0.466	0.500	351	0.422	0.495
Full-time faculty	628	0.909	0.288	283	0.965	0.185	345	0.864	0.344
Faculty has PhD degree	633	0.638	0.481	283	0.371	0.484	350	0.854	0.353
Full Professor	632	0.171	0.377	283	0.141	0.349	349	0.195	0.397
Associate Professor	632	0.538	0.499	283	0.399	0.491	349	0.650	0.478
Assistant Professor, Lecturer, or RA	632	0.291	0.455	283	0.459	0.499	349	0.155	0.362
Went to elite university for highest degree obtained	593	0.609	0.488	282	0.702	0.458	311	0.524	0.500
Majored in math or physics for highest degree	591	0.663	0.473	282	0.635	0.482	309	0.689	0.464
Number of years teaching (bottom tercile in country)	631	0.288	0.453	282	0.262	0.441	349	0.309	0.463
Number of years teaching (middle tercile in country)	631	0.372	0.484	282	0.422	0.495	349	0.332	0.472
Number of years teaching (upper tercile in country)	631	0.339	0.474	282	0.316	0.466	349	0.358	0.480

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